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Adaptive state-space model for ultra-precision feed axis

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Abstract

One method to produce surfaces with optical properties is the ultra precision cutting. This method allows to create surfaces not only with a roughness of few nanometers but also with low form deviations. Beside the use of advanced cutting technologies with diamond tools the path of the cutting edge is controlled very precisely. The main measures used to attain this precision are the increase of the base accuracy of the machine tool, the protection against environmental influences especially the temperature, and the prevention of dynamic loads on the machine tool. However, the last point in particular is realized by slow and smooth motions of the machine axes, which result in very long processing times of multiple hours to days per work piece. One method to increase the velocities and the accelerations is to predict and compensate the resulting tool path error. This requires a precise model of the machine tool. The parameters of this model need to be identified accurately. Furthermore, the precision of the model can be increased if the parameters are not only identified once, but repeatedly. This enables to adapt the model to parameter changes, which occur due to external and internal influences like temperature shifts, mass change and wear. For this purpose a model is built, which consists of two state-space submodels that represent the motion band and residual band features separately. The parameters of this model are adjusted by the prediction error method. The reaction time between the change of a parameter in the physical world and the adjustment of the related parameter value in the model must be short enough, so that the dynamic tool path error is kept inside the tolerance. This time period limits the bandwidth of available measurements. With this limitation of the dataset, the parameter identification becomes even more difficult. Still, to achieve accurate estimations of the parameters the search space for the identification is reduced by limiting the single parameters of the model. In this work this method is applied to an experimental setup. The precision of this approach is analyzed under varied conditions.

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Keywords: ultra precision machining; adaptive control; state-space model; prediction error method

1. Introduction

Parts with surface roughness values of few nanometers as well as form deviation values of few micrometers can be manufactured by ultra precision milling [1]. In these processes a main factor for the resulting roughness is the kinematic roughness, which is basically the imprint of the path and outer diameter of the cutting tool on the processed

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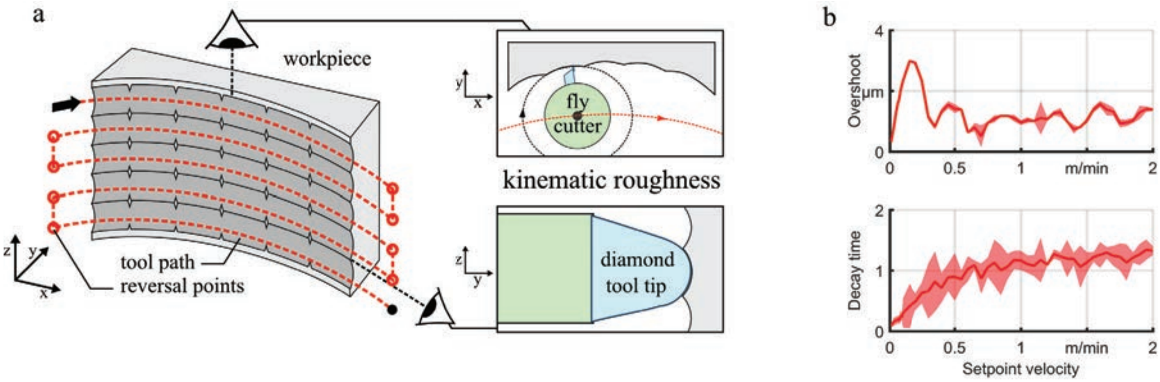

Fig. 1. Sources of long processing times. (a) Raster milling tool path and kinematic roughness (not to scale). (b) Dynamic deviation of an ultra precision feed axis.

surface. In, for example, a raster milling process the kinematic roughness is kept low by placing the single cuts of the cutter close to each other [2]. This requires very long tool paths with many reversal points, e.g. see Fig. 1b.

This is especially problematic, since loads on the machines feed axes need to be kept low to reduce vibrations and position deviations. For instance, even low velocities or accelerations induce a relatively large position overshoot in positioning tests, see Fig. 1a. Furthermore, this position deviations need a long time to decay, see Fig. 1a. The resulting low applicable velocities and long decay times as well as the long tool paths result in very long processing times.

To decrease the production times model based control methods are necessary to compensate the deviations and vibrations even at higher velocities. However, since the compensation results depend on the representation accuracy of the model, a model is necessary that meets the requirements and especially the resolution of ultra precision manufacturing.

The representation accuracy of a model is mainly determined by its structure and its parameters. The structure affects the accuracy by how precise it is able to reproduce the behavior of the kind of physical entity. The parameters affect the accuracy by how precisely they are adjusted. Typically, in the practical realization of a model both the model structure and the parameters values identification exhibit errors. The structure because it is based on isolated assumptions, which usually contain simplifications and are incomplete. The parameters because they can not be estimated with infinite accuracy. Further, the real parameters may change over time, which is caused by external influences that are not part of the model structure.

Nomenclature

n	degree of the state space model
x	state vector
t	time
u	model input
A	state matrix
B	input matrix
C	output matrix
e	deviation of the model
θ_{est}	estimated parameters
y_{mea}	measured output of the feed axis
w_{est}	window size of the estimation
p_{est}	parameter change limit

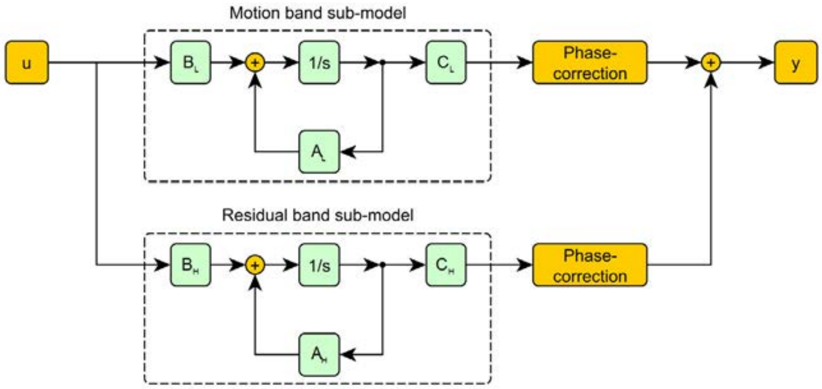

Fig. 2. Model structure

While a representation accuracy as high as possible is desirably for compensation it comes with high costs. These concern both the identification of the structure and the parameters values as well as the numerical handling during application. This becomes more likely with increasing accuracy requirements. One method to reduce this problem is to estimate the parameters of the model at runtime with actual measurements. The validity of such models is limited to a shorter period of time but they are able to adapt to conditions that are not explicitly mapped in the initial model. In the following a method for such an adaptive model for a single feed axis is presented and tested in experiments.

2. Model structure

The model structure of the feed axis consists of two sub-models. The motion band sub-model (MBSM) calculates the rough movement of the feed axis, while the residual band sub-model (RBSM) describes vibrations and corrects deviations of the MBSM. This enables the estimation of the parameters of the sub-models in individually suitable cycle times.

As mathematical representation of sub-models state-space models are used. In state-space models the system is expressed as n state-variables which are combined to the state-vector x. Each state variable can be considered as an energy storage of the system, which records the influence of past inputs to the actual state. A state vector at a time t for an input vector u can be calculated as:

$$\dot{x}(t) = Ax(t) + Bu(t) \tag{1}$$

A is the state matrix that defines how the single state variables interact and B is the input matrix that defines how the input influences the state variables. The output y of the model can be calculated from the state vector with the output matrix C.

$$y(t) = Cx(t) \tag{2}$$

The complexity of the model is set by the number of state variables n, which also influences the maximum number of parameters, especially the ones contained in A, since A is a n by n matrix. The outputs of the MBSM and the RBSM parts are phase corrected and are added up to the final result. The complete model is shown in Fig. 2.

The inital parameters for the model of the experimental setup are estimated similar to the method explained in chap. 3 but with a single static measurement without parameter variation. The results are parameters and states that have no direct connection with the physical world but are more of a generic nature. This process differs from the final setup with an ultra-precision machine axis. In that case the inital model is the result of an analytic process. However, that model will also be highly reduced and the parameters lose their physical meaning as well.

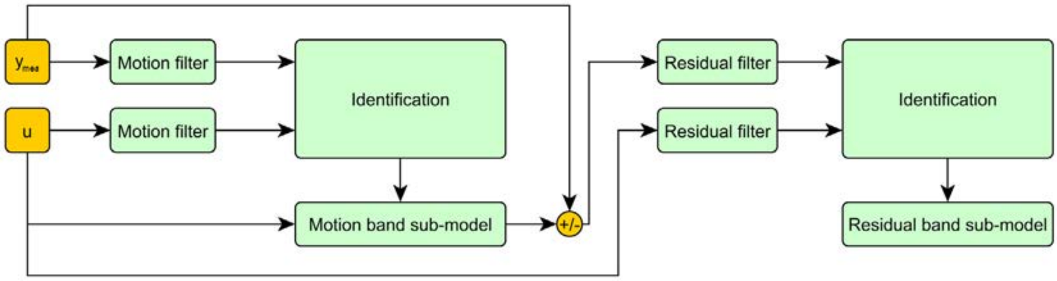

Fig. 3. Parameter identification principle

3. Parameter estimation

The parameter estimation method used for the adaptation of the model is based on the prediction error method (PEM) [3]. To estimate the parameters at a time t the outcome of the model at time $t+1$ is calculated and compared to the measurements at that time to calculate the deviation e. The main task is to find the parameters θ_{est} in the set of all parameters θ, so that $e(\theta_{est})$ becomes minimal. Since it is not possible to calculate all possible solutions a numerical approximation is nescessary. In this work the Levenberg-Marquardt method, which is essentially a regulated least-square method, is used to calculate θ_{est} [4].

To estimate the parameters of the MBSM and RBSM separately the input u and the measurements of the system y_{mea} are filtered before the PEM is applied. For the MBSM a equiripple finite impulse response (FIR) filter of order 422 is used, which is tuned to suppress frequencies above 20 Hz. The filtered values are used to estimate the parameters θ_{LF} of the MBSM. The new parameters are then used to simulate the output of the model based on the unfiltered input u. The deviation between the simulation and the measurements is then used for the estimation of the MBSM. First the devations and the inputs are filtered with an equiripple FIR-filter of order 506, which surpresses frequencies above 200 Hz. After that, the PEM is applied to identify the MBSM parameters θ_{HF}. The process is illustrated in Fig. 3.

As input for the parameter estimation a window of the input u as well as the measurements is used with a fixed size of w_{est} samples. The parameters are estimated in each window individualy to react to parameter variation of the system. Not every parameter estimation results in more accurate parameters. This depends beside others on the informations that are contained in each individual window. Hence, after each estimation the accuary of the estimated parameters are compared to the old ones and the parameters with less deviations are choosen as new model parameters. Further, to decrease the search space and to make the estimation more robust the change of each parameter is limited to a fixed percentage value p_{est} for every window. This increases the robustness, because only small variation of the parameters are expected. Hence, estimations that require a large change of one of the parameters is most likely faulty. The parameters w_{est} and p_{est} are different for the MBSB and RBSM.

4. Experimental setup

To validate the identification algorithm a simplified physical model was set up with a piezo stage “NanoCube”(P-611.3, Physik Instrumente). The object of observation is the z-Axis of the piezo stage and the variable parameter is the weight that is mounted on the NanoCube. The input to the piezo stage as well as the internal position sensor of the piezo stage are measured and used for the parameter estimation. As setpoint position a rectangle function is applied with an amplitude of $50\,\mu m$. The rectangle function is repeated several times from the same start position. The time between each rectangle is one second. The motions are performend in open-loop controll mode. An example for the input and output is shown in Fig. 4.

To achieve a single measurement with changing parameters the rectangle function for different weights are recorded separately. These are combined to a single long measurement. This reduces the influence of the mounting process to change the weight on the parameter estimation.

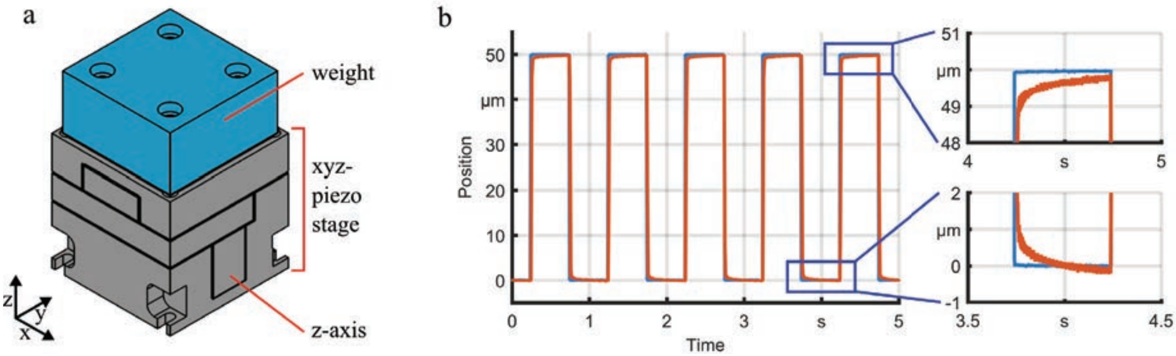

Fig. 4. (a) Experimental setup. (b) Position of the piezo stage.

5. Measurements

5.1. Limits for the parameter estimation and window size

First object of observation are suitable p_{est} values to limit the allowed parameter changes and the estimation window size w_{est}. To attain these values a single measurement with a single parameter change and nine consecutive rectangles is calculated with the parameter estimation for different combinations of p_{est} and w_{est}. The sqare mean deviation between the adaptive model and the original measurement evaluate the quality of the estimation. Further, the absolute mean deviation is calculated separately for the first, second and last thirds of the mesurements to give an impression of the deviation at different timesteps of the parameter estimation. The result for the MBSM is shown in Fig. 5.

The mean error is highly dependent on the window size w_{est}. Values within an intervall of 1200 to 3600 points result in in moderate deviations. Lower values produce significant high errors while larger values slightly increase the error. In contrast, p_{est} does not contribute to the mean error. However, since only small parameter changes are expected later in the application phase of the model the value for p_{est} is choosen as small as possible. For further investigations a value of 2500 points is choosen for w_{est} and a value of 15% for p_{est}. With the results of the MBSM the process is repeated for RBSM, Fig. 6.

The result for the RBSM are quite different compared to the MBSM. The mean error is effected both by the window size and the amount of allowed parameter changes. In this case suitable values are found by w_{est} = 1500 points and p_{est} = 15%.

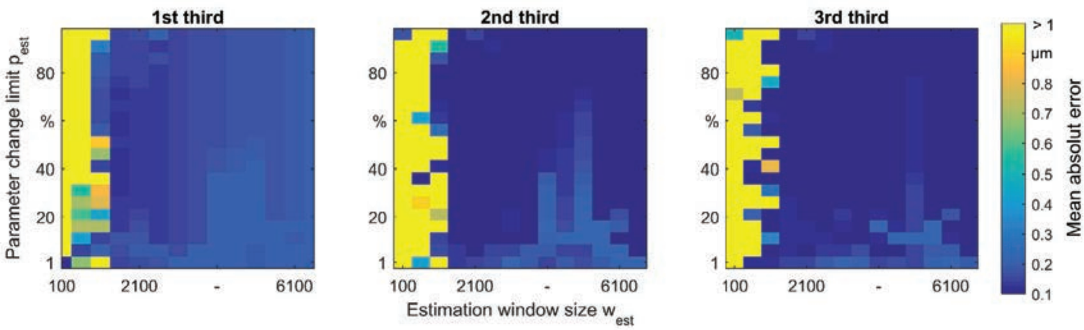

Fig. 5. Mean error for different parametersets

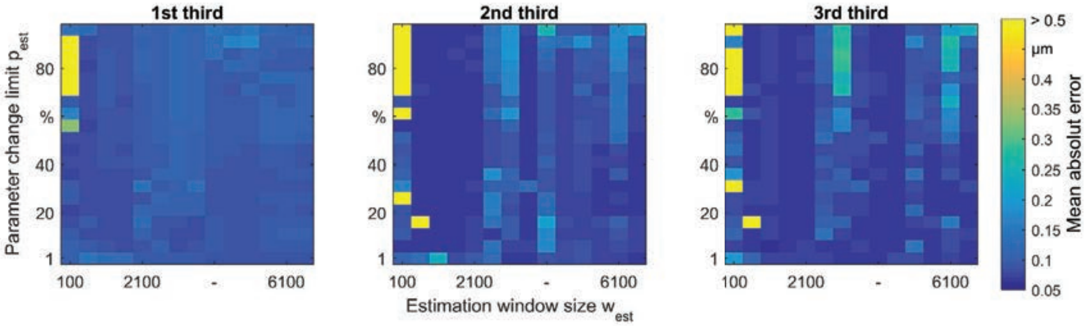

Fig. 6. Mean error for different parametersets

5.2. Variable parameters

For the last test the weight in the experimental setup is set to seven different values between 0 g and 125 g. For each weight five consecutive rectangular motions are measured and combined to a single measurement as described above. The parameter estimation is calculated with the values found in chap. 5.1. For each individual rectangular motion the absolute mean error, standard deviation and absolute maximum error is calculated. This is done for the static model without parameter estimation and the adaptive model. The result is displayed in Fig. 7.

The static model has a mean absolute error of about 0.26 μm in the MBSM, which is slightly reduced by the RBSM to roughly 0.2 μm. More noticable are the effects of the RBSM in the standard deviation, which is reduced from about

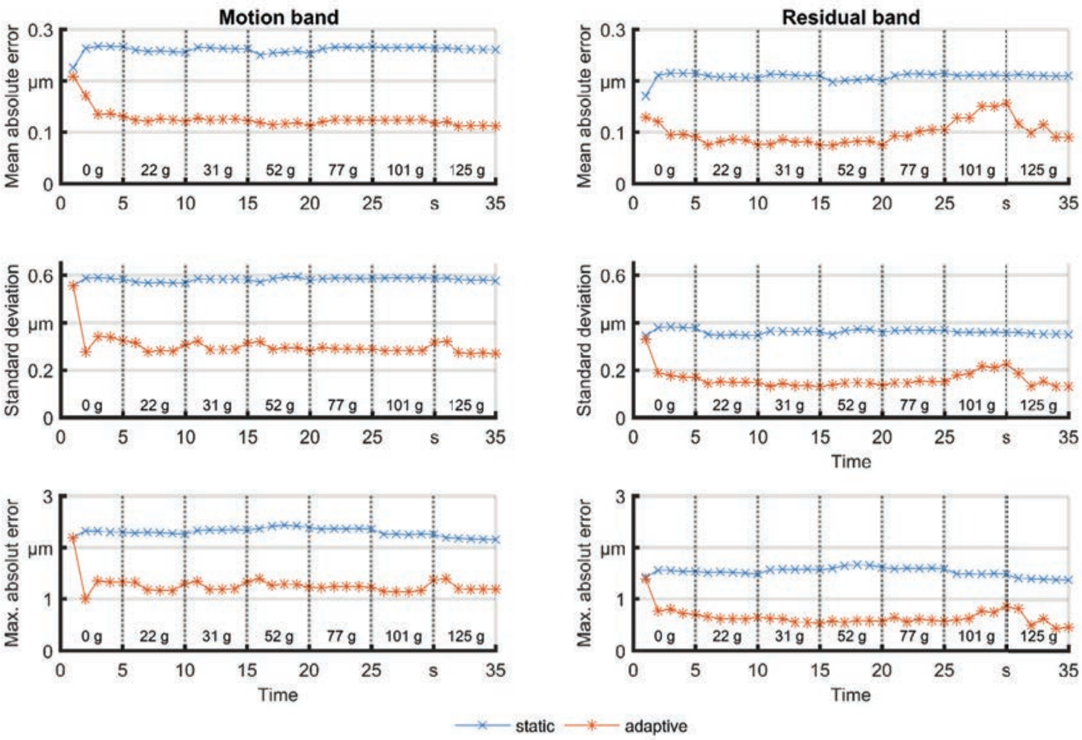

Fig. 7. Error comparison of the static and adaptive model. Vertical lines indicate the changes of the additional mass.

$0.6\,\mu m$ to under $0.4\,\mu m$. The deviations that are caused by the parameter variation are most visible in the maximum absolut error.

In comparison the adaptive model has already a large reduction at the part without paramater variation. For instance, the mean absoulte error is reduced to near $0.1\,\mu m$. This is most likely an result of inital parameter values that do not accurately fit the model to the actual system. One explaination for this are changes of the experimental setup, which occurred in the time between the calculation of the initial parameters and the parameter variation experiments, like changes of room temperature. Another explanation is that the inital parameters are calculated with a shorter measurement and were optimized by the parameter estimation. However, both cases might occur in the final setup on a ultra precision machine tool. The adaptive feature of the model is able to heal this decrepancy.

The influence of the parameter variation is visible in the adaptive model as well but mostly as short peaks at the points, where the weight is changed. This peak is reduced as soon as the parameters are adjusted. So, the influence of the parameter variation is largely suppressed, what is most noticable in the maximum absolute error of the RBSM. More research is required for the increasing error of the RBSM at the end of the measurement. The reason for this is unkown. The calculation time on a PC (Intel i5-4670 3.4 Hz) takes about 160 s for the 35 s measurements.

6. Conclusion

In this work an adaptive model for an ultra precision feed axis is developed and investigated. The proposed model consists of two sub-models which represent the motion band and residual band behavior. The parameters of the sub-models are adjusted separately while the feed axis is in motion. The method for the adjustment or rather estimation is based on the prediction error method, which is executed for single measurement windows with a fixed sample count. Further, the allowed parameter change in each window is limited to increase the robustness of the estimation. The method is verified on an experimental setup consisting of a piezo stage. The beavior can be varied by mounting different weights. After identifying suitable values for the estimation window size and the limits of the parameter change, the adaptive model reduces parameter deviations of the inital model as well as parameter changes during runtime. For example, the maximum absolute error is reduce from about $1.5\,\mu m$ to $0.5\,\mu m$.

For further research one point of interesst is which motions of the feed axis are suitable for the estimation, since it can be assumed that different motions in the estimation window result in different parameter estimations. For example, in the worst case no motion is measured in one estimation window and therefore the window contains no or only very little information about the system. On the other hand, motions like the rectangular function used in this work contain more information about the system. Furthermore, the parameter estimation should be extended to allow a continuous estimation with a floating window. This should result in a smoother transition between parameter changes and a shorter reaction time until parameter changes are detected. One possible method to achieve this without largly increasing the calculation time could be to distribute the single iteration steps of the prediciton error method over several estimation windows. This would be an important step towards a real time system. Lastly the method needs to be transfered to an actual ultra precision machine tool.

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